Paper

On the Design of the TCP/AQM Traffic Flow Control Mechanisms

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Abstract—Several aspects of the TCP/AQM system design are discussed that may affect performance of the network. Namely, due to decentralized structure of the network traffic flow control system in which traffic rate control tasks are delegated to autonomous agents, it may be possible for the agents to profitably re-engineer the TCP congestion control algorithm at the cost of the overall performance of the network. In this paper it is shown how the commonly applied TCP/AQM design procedures may give rise to mechanisms that are prone to attacks discreetly moving the network traffic flow away from the desired operating point. Furthermore, a short discussion is presented concerning the countermeasures that can be taken to reduce these effects.

Keywords—game theory, network security, TCP/AQM, traffic flow control.

1. Introduction

The transmission control protocol (TCP) congestion control algorithm adjusts packet transmission rate of a TCP node to locally observed network congestion signals, usually related to the rate of incoming transmission acknowledgment (ACK) messages. Since the congestion signals close the feedback loop between the interacting network nodes, thereby providing information about the utilization of the network's links, it is natural to interpret TCP and active queue management (AQM) mechanisms as elements of a distributed control system optimizing performance of the network.

In this brief paper the above point of view is taken to address a specific question regarding the expected performance of the popular TCP/AQM designs. Namely, a discussion is presented concerning the implications that *information asymmetry* between the interconnected network nodes may have on the overall performance of the network. The discussion is supported with the formal arguments that we have derived and studied in [1], [2].

The notion of information asymmetry which is being referred to here describes the setting in which the information about the control goals that are addressed at the level of a given node is not available to other nodes, but is essential for the efficiency of the interactions. It should be pointed out that this is a typical setting for the networked systems in general. Indeed, it results quite naturally from the decentralized structure of the network in which control tasks are delegated to autonomous elements of the system. It is the delegation of the tasks that creates an *information gap* in the system and severely limits the ability to control locally taken actions.

To be somewhat more specific about the addressed question, let us for a moment think of the network as of a distributed system of interacting plants, each one being controlled by an autonomous and intelligent (active) agent. An active agent should be identified with a network node administrator capable of implementing an arbitrary operating configuration of the node. Suppose next that we are faced with the problem of designing a distributed mechanism that leads the interacting plants, managed by the agents, to a solution of a given system performance optimization problem. Clearly, in the considered TCP/AQM networking context this amounts to designing traffic rate control and queue management algorithms that, if installed in the network's nodes, support reaching a desired operating point of the network. The performance optimization problem represents preferences defined with respect to the operating point, which in turn is specified by the performance index being optimized. This brings us to the observation that draws our attention here. A common engineering practice is to evaluate the system's performance by means of a scalarizing function, aggregating individual performance indices of the interacting plants. Indeed, under sufficient regularity conditions optimization of the scalarizing function leads to Pareto-optimal outcome of the addressed multiobjective problem, i.e., the problem in which each plant tries to reach its optimal performance subject to the interaction constraints. The question of our interest is related to the possibility of reaching the solution to the performance optimization problem. Namely, in the addressed asymmetric information environment the only way to calculate the value of the network-wide performance index, aggregating agents' performance, is to process information that the agents reveal in the course of their interactions. In other words, performance of the system can only be optimized if the preferences of the agents are known to the mechanism that coordinates the agents' interactions. However, since the agents remain autonomous in their decisions, they may find a way to reveal a profitably modified information on their performance, thereby taking advantage of the monopoly they have on the information regarding their individual goals. It, therefore, becomes clear that in such a case efficient performance of the system can be questioned.

In the following sections the above problem is addressed in the context of the TCP/AQM control system design. It is demonstrated that commonly applied design procedures may give rise to mechanisms that are prone to a specific kind of actions, or even intentional attacks, moving the network traffic flow away from the desired operating point.

These attacks may seem to resemble the well known TCP SYN flooding technique, exploiting the way of establishing a new TCP connection [3], [4]. However, as it is to be illustrated, in the considered case the architecture of attack is different and may result in *degradation of service* rather that in *denial of service* (DoS). In the following section the countermeasures are also discussed that can be taken by the designer of the TCP/AQM mechanisms to reduce the potentially adverse effects of distributed control under asymmetric information. Our results are built upon the models studied in [5]–[7], and recently in [1], [2]. Technical details concerning implementation of TCP and AQM algorithms can be found, e.g., in [8], [9]. For a survey of results on information asymmetry see e.g., [10].

2. Traffic Flow Control Mechanism Design

Consider a network that consists of E links shared by transmission streams originating from S sources. Each source $s = 1,\dots,S$ is associated with a connection that is realized between a specified source-destination pair of the network's nodes. The connection can be established by a collection of $P_s,\ s = 1,\dots,S$, paths. Multi-path routing, which is admitted in the considered setting, is defined by routing matrices $\mathbf{A}_s,\ s = 1,\dots,S$, consisting of elements $a_{spe} = 1$ if link e is used by the p-th route originating from source s and $a_{spe} = 0$ otherwise.
With each source there is associated a transmission performance index $U_s,\ s = 1,\dots,S$. The value $U_s(x_s)$ can be interpreted as a utility that transfer rate $x_s \geq 0$ has to the source. Similarly, with each link $e = 1,\dots,E$ there is associated a performance index C_e defining value of cost $C_e(y_e)$ at which network link serves flow $y_e \geq 0$ of incoming data.
A two-step design procedure will be now discussed that is usually applied to engineer a stable and efficient process of network traffic flow control. In the first step, a reference point for the design is defined to represent a preferred outcome of the network performance optimization problem. In the second step, based on the desired performance conditions satisfied by the selected reference point, a dynamic system is constructed that is guaranteed to converge to a neighborhood of the reference point. The definition of the dynamic system is then used as a design guideline for the algorithms implemented in the network.
Let us illustrate the above procedure. The basic problem that underlies current designs of TCP/AQM algorithms, mostly due to [5], [11], is defined as follows:

$$\texttt{SYSTEM}(\mathbf{U},\mathbf{A},\mathbf{c}):$$
$$\left|\begin{array}{ll} \text{maximize} & \sum_s U_s(x_s) \\ \text{subject to} & \mathbf{A}^T\mathbf{x} \leq \mathbf{c} \\ \text{over} & x_s \geq 0,\ s = 1,...,S, \end{array}\right.$$

where $\mathbf{c}^T = [c_1,\dots,c_e]$ is a vector of fixed capacities of the links. A problem `SYSTEM` defines the reference point for the design of distributed network flow control system. As it can be easily seen, the basic problem is *multi-objective*, with the objectives defined by the performance indices of the network elements given by functions $U_s,\ s = 1,\dots,S$, and $C_e,\ e = 1,\dots,E$. In the above formulation, efficient (undominated) solutions are searched for by means of a simple (utilitarian or maxisum) scalarization. For other interesting approaches see, e.g., [12]–[15]. Notice that a single path routing matrix $\mathbf{A}$ is used here. Furthermore, it follows that $C_e(y_e) = 0$ for $0 \leq y_e \leq c_e$ and $C_e(y_e) = +\infty$ whenever $y_e > c_e$.
The following sequence of arguments supports the construction of a distributed traffic flow control system that is intended to lead the network to a neighborhood of the reference point defined above. Suppose that each source submits to the network a bid $\theta_s \geq 0$ denoting willingness to pay for the traffic rate $x_s = \theta_s/\lambda_s \geq 0$, where $\lambda_s \geq 0$ can be regarded as a charge per unit traffic flow. Let us also assume that each source, *taking* $\lambda_s = \sum_e a_{se}\mu_e > 0$ *as given*, chooses θ_s that maximizes *payoff* related to the assigned transfer rate, i.e., it solves the problem:

$$\texttt{USER}_s(U_s,\lambda_s):$$
$$\left|\begin{array}{ll} \text{maximize} & U_s(\theta_s/\lambda_s) - \theta_s \\ \text{over} & \theta_s \geq 0. \end{array}\right.$$

Next, suppose that given the vector $\boldsymbol{\theta} = (\theta_1,\dots,\theta_S)$ of bids, the network calculates prices (Lagrange multipliers, congestion signals) $\mu_e \geq 0,\ e = 1,\dots,E$, and rates $x_s \geq 0,\ s = 1,\dots,S$, solving the problem:

$$\texttt{NETWORK}(\mathbf{A},\mathbf{c},\boldsymbol{\theta}):$$
$$\left|\begin{array}{ll} \text{maximize} & \sum_s \theta_s \log(x_s) \\ \text{subject to} & \mathbf{A}^T\mathbf{x} \leq \mathbf{c} \\ \text{over} & x_s \geq 0,\ s = 1,\dots,S. \end{array}\right.$$

The reason for application of the specific form of utility function, $U_s(x_s) = \theta_s \log(x_s)$, will become clear in a moment. Theorem 1, presented below, shows that under the assumption that the sources take the feedback signals $\bar{\boldsymbol{\lambda}}$ *as given*, a feasible network traffic flow can be found, which is arbitrarily close to solution of the problem $\texttt{SYSTEM}(\mathbf{U},\mathbf{A},\mathbf{c})$. Namely, the flow can be reached by a distributed algorithm that solves the problem $\texttt{NETWORK}(\mathbf{A},\mathbf{c},\boldsymbol{\theta}(t))$ at instant t and, on a larger time scale, drives $\boldsymbol{\theta}(t)$ to $\bar{\boldsymbol{\theta}}$ defining optimal solution to $\texttt{SYSTEM}(\mathbf{U},\mathbf{A},\mathbf{c})$.

Theorem 1: Suppose that U_s is an increasing, strictly concave and continuously differentiable function over $x_s \geq 0$ for $i = 1,\dots,n$. There exist vectors $\bar{\boldsymbol{\lambda}} = (\bar{\lambda}_1,\dots,\bar{\lambda}_n)$, $\bar{\boldsymbol{\theta}} = (\bar{\theta}_1,\dots,\bar{\theta}_n)$ and $\bar{\mathbf{x}} = (\bar{x}_1,\dots,\bar{x}_n)$ such that:

- $\bar{\theta}_s$ solves $\texttt{USER}_s(U_s,\bar{\lambda}_s)$, $s = 1,\dots,S$;
- $\bar{\mathbf{x}}$ solves $\texttt{NETWORK}(\mathbf{A},\mathbf{c},\bar{\boldsymbol{\theta}})$ and $\texttt{SYSTEM}(\mathbf{U},\mathbf{A},\mathbf{c})$;
- $\bar{\theta}_s = \bar{\lambda}_s\bar{x}_s$, $s = 1,\dots,S$;

Proof: For the proof see, e.g., [5]. ■

Based on the above result, a distributed traffic flow control algorithm can be derived from the following system of differential equations:

$$\mathtt{RATE}(\mathbf{A},\mathbf{q},\boldsymbol{\theta}):$$
$$\left|\begin{array}{l} \dfrac{\mathrm{d}x_s}{\mathrm{d}t}(t)=\kappa\left[\theta_s-x_s(t)\sum_e a_{se}\mu_e(t)\right],\ s=1,\ldots,S, \\ \mu_e(t)=q_e(\sum_s a_{se}x_s(t)),\ e=1,\ldots,E. \end{array}\right.$$

System $\mathtt{RATE}(\mathbf{A},\mathbf{q},\boldsymbol{\theta})$ describes a network-wide traffic rate adjustment process, $x_s(t),\ s=1,\ldots,S$, with feedback provided to each network node by congestion signals $\mu_e(t)$, $e=1,\ldots,E$. By construction, the system exploits the properties of the equilibrium point described in Theorem 1, applying function $\bar{U}_s(x_s)=\theta_s\log(x_s),\ s=1,\ldots,S,$ as a model of preference indicator applied by each traffic source. Precisely, the construction of the desired distributed control algorithm rests on the following result. Given a fixed signal $\theta_s,\ s=1,\ldots,S$, and a well-behaved and suitably designed function $q_e,\ e=1,\ldots,E$, system $\mathtt{RATE}(\mathbf{A},\mathbf{q},\boldsymbol{\theta})$ converges to minimum of function:

$$\sum_e\int_0^y q_e(s)\mathrm{d}s-\sum_s\theta_s\log x_s,\ \text{with}\ y=\sum_s a_{se}x_s. \tag{1}$$

It follows that by letting the sources periodically update signals θ_s, a neighborhood of solution to problem $\mathtt{SYSTEM}(\mathbf{U},\mathbf{A},\mathbf{c})$ can be reached. Indeed, suppose that each source applies the following control rule:

$$\theta_s(t)=x_s(t)U_s'(x_s(t)),\ s=1,\ldots,S, \tag{2}$$

where $U_s'\equiv \mathrm{d}U_s/\mathrm{d}x_s$. It can be demonstrated that the above evolution of $\boldsymbol{\theta}(t)$ defines TCP traffic rates $\mathbf{x}(t)$ that converge to a stable point $\bar{\mathbf{x}}$ minimizing:

$$\sum_e\int_0^y q_e(s)\mathrm{d}s-\sum_s U_s(x_s),\ \text{with}\ y=\sum_s a_{se}x_s. \tag{3}$$

For a suitable choice of function $q_e,\ e=1,\ldots,E$, representing an AQM policy, the above function arbitrarily closely approximates objective in $\mathtt{SYSTEM}(\mathbf{U},\mathbf{A},\mathbf{c})$. Thus vector $\bar{\mathbf{x}}$ of traffic rate solves relaxation of the network performance optimization problem. Details concerning practical implementations of the above algorithm can be found, e.g., in [16]–[22].

Example: FAST TCP algorithm

To control the rate at which packets are transmitted, the FAST TCP algorithm updates the amount of data transmitted into the network at a given time, based on the observed average round-trip time and average queuing delay [23]–[18]. The amount of transmitted data is defined by the value of the TCP networking stack variable denoting the congestion window size, $w_s\geq 0$. Precisely, a FAST TCP node s adapts control variable w_s according to the following rule:

$$w_s(t+1)=\gamma\left(\frac{d_s w_s(t)}{d_s+\lambda_s(t)}+\theta_s\right)+(1-\gamma)w_s(t), \tag{4}$$

where $d_s\geq 0$ denotes the round-trip propagation delay, $\lambda_s\geq 0$ denotes the round-trip queuing delay observed by source s and $\gamma\in(0,1]$. The algorithm can be proved to converge to the following operating point of the network:

$$\bar{w}_s=\bar{\theta}_s+\bar{x}_s d_s,\ \bar{\lambda}_s=\bar{\theta}_s/\bar{x}_s=\bar{U}_s'(\bar{x}_s). \tag{5}$$

In simple terms, in the above equilibrium point source s maintains $\bar{\theta}_s=\bar{x}_s\bar{\lambda}_s$ packets in the buffers along its path and $\bar{x}_s d_s$ packets in the transmission lines. It should also be noticed that for the equilibrium to be practically implementable, it is necessary that the total amount of buffering in the network be at least $\sum_s\bar{\theta}_s$, i.e., the transmission delay (or, so called, budget) balancing condition must be satisfied.

3. Anticipative Flow Control: Design and Countermeasures

By the above description, the TCP/AQM flow control system defines target equilibrium conditions for the network. Precisely, these conditions are built into the TCP/AQM control rules in order to lead the network of interacting nodes to the solution of problem $\mathtt{NETWORK}$, desired by the control system designer. It will be now argued that in the considered distributed environment the TCP/AQM control system may be prone to *attacks* if the concept of information asymmetry is not taken into account in the control system design.

The TCP/AQM mechanisms are commonly known to the network users managing their network nodes. At the same time, the network users are autonomous in choosing their protocol implementations and are capable of modifying the parameters of the applied traffic flow control algorithms. In other words, there exists a natural information asymmetry between the network users. In particular, such an asymmetry exists between the network users adjusting their transmission rates and the network manager allocating traffic forwarding resources. Let us stick to this setting to illustrate how the information asymmetry may create incentives for the network users to implement *feedback-anticipating* strategies in their rate control algorithms.

The idea which underlies the construction of such control rules is quite simple: the network users should reveal to the network a suitably reduced level of demand for traffic flow.

Indeed, since the network is required to satisfy the observed demand, its reduced level may give rise to lower levels of congestion signals that provide network-wide feedback on the utilization of resources. As a result, the network users may expect to receive an improved level of payoffs (individual performance indices) from the traffic rates admitted by the network.

To implement the above anticipative rate control strategy, a network user may modify the rule according to which $\theta_s(t)$ is updated in the original TCP design. Namely, source s may submit signal:

$$\theta_s(t) = x_s(t)\tilde{U}_s'(x_s(t)), \tag{6}$$

where $\tilde{U}_s'(x_s(t)) < U_s'(x_s(t))$. If the above bidding rule is applied, the network is informed that marginal performance gain that source s receives from the rate at which it sends that traffic is lower than it is in reality. Precisely, this information is propagated in the network through the congestion window size forming burstiness of the traffic. As a consequence the network's operating point is modified.

The above conclusion can be clearly illustrated with the example of equilibrium point conditions given by Eq. (5). Under anticipative rate control one may expect a neighborhood of the following operating point to be reached:

$$\hat{w}_s = \hat{\theta}_s + \hat{x}_s d_s, \; \hat{\lambda}_s = \hat{\theta}_s/\hat{x}_s = \tilde{U}_s'(\hat{x}_s) < \bar{U}_s'(\bar{x}_s) = \bar{\theta}_s/\bar{x}_s. \tag{7}$$

This observation shows that under anticipative rate control the network traffic flow should be expected to deviate from the solution to `NETWORK` problem. Also, notice that by the above description the strategy may be quite easily implemented by the administrator of a network node.

Clearly, an experimental study is necessary to identify performance characteristics of the discussed process, especially under traffic demand shaped by a stochastic process. Nonetheless, formal studies suggest that one may expect to observe substantial performance variations. An important game-theoretic model of outcomes reachable under the discussed strategy can be found in [6], [7]. Namely, it is demonstrated that the network-wide efficiency of outcomes may fall by approximately 1/3 relative to the reference solution of problem `SYSTEM`. In [2] the proposed model is further developed to investigate the outcomes that are reachable *individually* by each agent. In particular, referring to the reference point properties, in equilibrium of the traffic flow control process with feedback-anticipating agents competing for a single link:

- each agent communicates reduced demand to the network, which leads to reduced charge per unit traffic flow and reduced utilization of the link capacity;
- some of the agents (but not all) may be allocated improved rates, in case of which they also receive improved payoffs;
- some of the agents (but not all) may receive improved payoffs with reduced rates;
- commonly applied truthful preference revelation cannot be strictly dominated by commonly applied anticipative strategy with respect to the traffic rates individually received by each agent.

In light of the above predictions, an immediate question arises whether it is possible to reduce the potentially adverse effects of the feedback-anticipation and keep the operating point of the traffic flow in a neighborhood of the reference point. This issue is addressed in [1]. The environment in which the network performance optimization problem is addressed here, is assumed to be characterized by the following properties. First, the problem can be decomposed with respect to *control* (independent) variables $x_i, \; i = 1,\ldots,n$, and *interaction* (dependent) variables $y_j, \; j = 1,\ldots,m$. Second, the problem of calculating x_i is delegated to a designated agent $i = 1,\ldots,n$, whereas the interaction variables $y_j, \; j = 1,\ldots,m$, remain managed by the network manager. Finally, in order to calculate control inputs $x_i, \; i = 1,\ldots,n$, the agents actively exploit the first-order optimality conditions satisfied by the commonly known reference point, i.e., a solution to the network performance optimization problem. The following theorem is proved.

Theorem 2: Consider the following problem:

$$\begin{array}{l} \mathtt{P}(f_j, \; j=0,\ldots,m): \\ \left| \begin{array}{ll} \text{minimize} & f_0(\mathbf{x},\mathbf{y}) \text{ over } (\mathbf{x},\mathbf{y}) \in \mathbb{R}^n \times \mathbb{R}^m \\ \text{subject to} & f_j(\mathbf{x},\mathbf{y}) = 0, \; j = 1,\ldots,m, \\ & n,m > 0, \; f_j \in \mathscr{C}^2, \; j = 0,\ldots,m. \end{array} \right. \end{array}$$

Suppose that $f_j(\mathbf{x},\mathbf{y}) = \sum_i f_{ji}(x_i) + g_j(\mathbf{y})$ for $j = 0,\ldots,m$. Let $\bar{\mathbf{z}} = (\bar{\mathbf{x}},\bar{\mathbf{y}})$ be a point for which the second-order necessary optimality conditions for P hold with $\det \nabla_{\mathbf{y}} \mathbf{F}(\bar{\mathbf{x}},\bar{\mathbf{y}}) \neq 0$. Suppose also that for $\mathbf{x} \in \mathbb{B}_\varepsilon(\bar{\mathbf{x}}) = \{\mathbf{x}\colon \|\bar{\mathbf{x}} - \mathbf{x}\| \le \varepsilon, \; \varepsilon > 0\}$ functions $\eta_i, \; i = 1,\ldots,n$, are defined by:

$$\begin{cases} \dfrac{\partial \eta_i}{\partial x_i}(\mathbf{x}) = \sum_j p_j(\mathbf{x}) \dfrac{\partial f_{ji}}{\partial x_i}(x_i), \; i = 1,\ldots,n, \\ \mathbf{p}(\mathbf{x}) \equiv -\left(\dfrac{\partial \mathbf{F}^T}{\partial \mathbf{y}}(\mathbf{x},\mathbf{Y}(\mathbf{x})) \right)^{-1} \dfrac{\partial f_0}{\partial \mathbf{y}}(\mathbf{x},\mathbf{Y}(\mathbf{x})), \\ \mathbf{F}(\mathbf{x},\mathbf{Y}(\mathbf{x})) \equiv 0, \end{cases} \tag{8}$$

and for any $\mathbf{v} \in \mathbb{R}^n \setminus \{0\}$ the following condition holds:

$$\mathbf{v}^T \frac{\partial \mathbf{Y}^T}{\partial \mathbf{x}}(\bar{\mathbf{x}}) \frac{\partial^2 H}{\partial \mathbf{y}^2}(\bar{\mathbf{x}},\mathbf{p}(\bar{\mathbf{x}})) \frac{\partial \mathbf{Y}}{\partial \mathbf{x}^T}(\bar{\mathbf{x}})\mathbf{v} > 0, \tag{9}$$

where $H(\mathbf{x},\mathbf{p}(\mathbf{x})) = f_0(\mathbf{x},\mathbf{Y}(\mathbf{x})) + \mathbf{p}(\mathbf{x})^T \mathbf{F}(\mathbf{x},\mathbf{Y}(\mathbf{x}))$. Then $\bar{\mathbf{z}}$ is an isolated solution to problem P and also a unique solution to system:

$$\begin{array}{l} \mathtt{PAYOFF}_i(f_{0i},\bar{x}_i,\mathbf{x}_{-i}), \; i = 1,\ldots,n: \\ \left| \begin{array}{ll} \text{minimize} & J_i(x_i,\mathbf{x}_{-i}) = f_{0i}(x_i) + \eta_i(\mathbf{x}) \\ \text{over} & x_i \in \mathbb{B}_\varepsilon(\bar{x}_i), \end{array} \right. \end{array}$$

where $\mathbf{x}_{-i} = (x_1,\ldots,x_{i-1},x_{i+1},\ldots,x_n)$.

Proof: Presented in [1]. The proof is based on the classic elimination approach, according to which the constrained problem is reduced to an unconstrained one with m dependent (interaction or basic) variables expressed in terms of n independent (control) variables. At the same time, however, it should be emphasized that in the analyzed environment the applied approach serves as a *model of reasoning* that is followed by intelligent agents exploiting the commonly available information on the performance optimization goal. ∎

Theorem 2 specifies sufficient conditions for implementation of a regular local solution to problem P in a Nash equilibrium point of a noncooperative feedback-anticipation game. Precisely, the theorem shows how to design payoffs $J_i,\ i=1,\dots,n$, in order to reach solution to problem P in a Nash equilibrium point. By construction the payoffs remain invariant with respect to the first-order variations of the feedback variables, modeled by $\mathbf{p}(\mathbf{x})$. This property maintains compatibility of the performance optimization goal with the private goals of the interacting agents. Furthermore, the theorem describes a game (or control mechanism) design procedure that exploits local properties of a feasible solution for problem P in order to define a *collection* of games (mechanisms) that coordinate interactions of the feedback-anticipating agents in the neighborhood of the feasible solution.

Detailed analysis of the equilibrium point defined by a solution to system $\mathtt{PAYOFF}_i,\ i=1,\dots,n$, supports the following collection of conjectures:

– if all agents apply the feedback-anticipating strategy to calculate the controls optimizing payoffs $J_i,\ i=1,\dots,n$, then they implement the performance optimization goal by autonomously acting in their own best interest (incentive compatibility condition);

– since no profitable distortions of the feedback variables (i.e. misrepresentations of preferences) are reachable under the applied rules of the game, it is optimal for the agents to calculate their controls by taking the best responses to the observed *values* of feedback variables;

– in equilibrium the feedback (dual) variables are assigned values equal to those that would be obtained if the network had enough information to solve P in a centralized manner.

The above conclusions provide motivation for the search of iterative and distributed procedures that may lead the strategically interacting agents to the operating point, maximizing performance of the network under asymmetric information. Indeed, since the non-anticipative control is equivalent to the optimal anticipative one in equilibrium point of the game defined by system $\mathtt{PAYOFF}_i,\ i=1,\dots,n$,, the direct preference revelation strategy, given by Eq. (2), may be used at the network traffic source level to control the rate of transmission. However, for this strategy to be implemented by the feedback-anticipating agents, it is necessary for the network to provide sufficient rate control incentives to the agents. By Theorem 2 these incentives can be given the following form:

$$\bar{\eta}_s(\lambda_s,x_s)=x_s\lambda_s-\bar{h}_s(x_s),\ i=1,\dots,n, \tag{10}$$

$$\bar{h}_s(x_s)=\sum_e\int_0^{x_s}a_{se}s\mathrm{d}q_e(s+\sum_{k\neq s}a_{ke}x_k)-b_s(\mathbf{x}_{-s}), \tag{11}$$

where $\lambda_s=\sum_e a_{se}q_e(y_e),\ s=1,\dots,S$, and $b_s(\mathbf{x}_{-s})$ is the transmission delay (or budget) balancing component. Thus in equilibrium source s transmits packets at rate $\bar{x}_s$ if it incurs transmission cost $\bar{\eta}_s(\bar{\lambda}_s,\bar{x}_s)$. The corresponding charge per unit traffic flow for i should, therefore, be defined by:

$$\lambda_s^*=\max\{\bar{\lambda}_s-\bar{h}_s(\bar{x}_s)/\bar{x}_s,0\}. \tag{12}$$

This result can be given the following interpretation. Suppose that $\lambda_s^*>0$ with $\bar{h}_s(\bar{x}_s)>0$ for some $\bar{x}_s>0$. In such a case, source s is motivated to adjusts its rate to $\bar{x}_s$ if it *observes* average delay of $\lambda_s^*<\bar{\lambda}_s$, which would correspond to $\theta_s^*=\bar{\theta}_s-\bar{h}_s(\bar{x}_s)<\bar{\theta}_s$ packets maintained in the buffers along the routing paths for $w_s^*=\bar{w}_s-\bar{h}_s(\bar{x}_s)<\bar{w}_s$. Hence, the network motivates the source to optimally adjust its rate by providing to it the quality of service (QoS) parameters that are improved in comparison to those arising as a solution to NETWORK problem. This implies that the network must be capable of providing differentiated services to the interacting sources, for example by applying suitable active queue management (AQM) techniques.

Although the above requirements can be supported by the currently available networking technology, it is clear that the traffic engineering cost imposed by the mechanism may be substantial. Indeed, game theory shows that for a wide class of problems it is impossible to avoid the costs of Nash equilibrium design; for details see, e.g., [25]–[28]. Namely, gains from reaching a desired solution to the performance optimization problem need not balance the losses corresponding to the introduction of incentives that make this solution attainable in a noncooperative game, i.e., under asymmetric information. These costs must be incurred by the coordinator through violation of the *balancing* condition, or by the agents through violation of the *rational participation* constraint. Theorem 2, presented above, can be applied to give quantitative characterization of theses costs as well. In general, in the considered networking context Theorem 2 implies that:

– under anticipative traffic flow control it may be more desirable for the network manager to reach a suboptimal traffic flow than the optimal one requiring additional coordination costs;

– costs of counterspeculation can be managed, at least to some extent, by a proper design of coordination instruments and by a choice of interaction variables in the network, where the interaction variables represent capacities of the actively managed queues in the network;

– cost of reaching the reference point may discourage some of the agents from participation in the game, i.e., some of the sources may receive payoffs that are below their expectations;

– counterspeculation may be an option for the network manager only if the balancing condition can be satisfied.

The above costs of reaching the desired operating point of the network can be intuitively related to the information monopoly that exists in the considered class of distributed systems. Since it is not possible to fully eliminate the costs of enforcing incentive compatibility, these costs may play the key role in the control system design decision-making process.

4. Design Framework For Traffic Flow Control Mechanisms

The discussion in the previous sections brings us to the concept of a procedure that can be applied to engineer a distributed process of traffic flow control under asymmetric information. The idea that underlies the design is to refer to the constructions described by Theorem 2 in order to harmonize interactions of the feedback-anticipating agents and incentivize them to reach the reference solution to the network performance optimization problem. Let us now give an overview of the procedure. The question of algorithm design and implementation is omitted here, since several related remarks and suggestions have already been made in the previous sections.

First, a reference point for the design should be defined to describe a desired performance profile of the network. The following (quite standard) optimization problem can be proposed to serve as a model of preferences defined with respect to the operational performance of the network:

$$\texttt{TRAFFIC}(\mathbf{U},\mathbf{C},\mathbf{A}):$$

$$\left|\begin{array}{ll}\text{maximize} & \sum_s U_s(\sum_p x_{sp}) - \sum_e C_e(\sum_s\sum_p x_{sp}a_{spe}) \\ \text{over} & x_{sp}\geq 0,\ s=1,\ldots,S,\ p=1,\ldots,P_s.\end{array}\right.$$

Thus the reference point for the design is defined as a solution $\bar{\mathbf{x}}$ to problem $\texttt{TRAFFIC}(\mathbf{U},\mathbf{C},\mathbf{A})$. Notice that the multipath routing problem is considered here in which flows originating from source s may follow more than one route to destination.

As we have already argued, due to decentralized nature of the network, specifications of the utility functions $U_s,\ s=1,\ldots,S$, and the cost functions $C_e,\ e=1,\ldots,E$, are known only locally. To engineer a network-wide control process in the addressed asymmetric information environment we propose to follow a coordination-based approach in which an attempt is made to decompose the reference solution and to build it into the local control rules at the level of networking elements. For this purpose, two sets of auxiliary problems can be defined associated with the network links and traffic sources, respectively.

4.1. Link-Control Problem

The first set of problems is given the following form:

$$\texttt{LINK}_e(y_e),\ e=1,\ldots,E:$$

$$\left|\begin{array}{ll}\text{maximize} & \eta_e(z,y_e)-Q_e(z) \\ \text{over} & z\geq y_e.\end{array}\right.$$

Problem $\texttt{LINK}_e$ is intended to provide a description of the following link behavior pattern: based on a observed incoming data transfer rate $y_e\geq 0$ select a feasible operating service rate $z\geq 0$ such that QoS targets are met. The corresponding mechanism design problem is to construct functions η_e and Q_e for each $e=1,\ldots,E$ that make the above behavior pattern implementable.

4.2. Transfer Rate Control

The second set of optimization problems is given the following form:

$$\texttt{SOURCE}_s(\boldsymbol{\mu}),\ s=1,\ldots,S:$$

$$\left|\begin{array}{ll}\text{maximize} & U_s(z_s(\mathbf{x}_s))-\bar{\eta}_s(\boldsymbol{\mu},\mathbf{x}_s) \\ \text{subject to} & x_{sp}\geq 0,\ p=1,\ldots,P_s.\end{array}\right.$$

Problem $\texttt{SOURCE}_s(\boldsymbol{\mu})$ models behavior of source s adjusting its data transfer rate $z_s(\mathbf{x}_s)$, distributed according to $\mathbf{x}_s$ along the set of routing paths, to the observed coordination signals $\boldsymbol{\mu}$ providing information about utilization of resources in the network. In this case the corresponding design problem is to construct functions U_s, z_s and $\bar{\eta}_s,\ s=1,\ldots,S$ that support efficient adaptation of transfer rates over optimized set of paths, and lead the sources to the reference solution of problem $\texttt{TRAFFIC}(\mathbf{U},\mathbf{C},\mathbf{A})$.

5. Summary

Our intention here was to point out several aspects of the TCP/AQM system design that may affect its performance. It has been argued that due to decentralized structure of the network traffic flow control system, in which traffic rate control tasks are delegated to autonomous agents and coordinated by means of the network congestion signals, it may be possible (for the agents managing the traffic sources) to profitably re-engineer the TCP congestion control algorithm at the cost of the overall performance of the network. Since the formulated conjectures have been derived from our theoretic considerations, we find it necessary to verify them experimentally. From this point of view this paper can therefore be taken as a proposal for further studies.

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